Automated Airborne Pest Monitoring of *Drosophila suzukii* in Crops and Natural Habitats

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Background

The fruit fly *Drosophila suzukii*, also known as the spotted wing *Drosophila*, has become a serious pest in Europe attacking many soft-skinned crops such as several berry species and grapevines since its spread in 2008 to Spain and Italy. An efficient and accurate monitoring system to identify the presence of *D. suzukii* in crops and their surroundings is essential for the prevention of damage to economically valuable fruit crops.

Objective

Existing methods for monitoring *D. suzukii* are costly, time and labour intensive, and typically conducted at a low spatial resolution. To overcome current monitoring limitations, we are developing a novel system consisting of sticky traps which are monitored by means of UAVs and an image processing pipeline that automatically identifies and counts the number of *D. suzukii* per trap location. In the future, the counts of *D. suzukii* flies should serve as input to a decision support system.

Training data

We collected a training dataset of annotated images containing *D. suzukii* flies on sticky traps. Over 2,000 images of *D. suzukii* flies (which was increased to over 12,000 with data augmentation) were used to train two deep learning models: AlextNet[1] and GoogLeNet[2]. Currently, our focus is on the detection of male *D. suzukii* flies, with their characteristic black spots on the wing tips (figure 1).

Figure 1. Male *Drosophila suzukii* fly with the typical black spots on the wing tips (left). Female *Drosophila suzukii* fly (right).

Figure 2. Example of training data.

The use of UAVs for monitoring

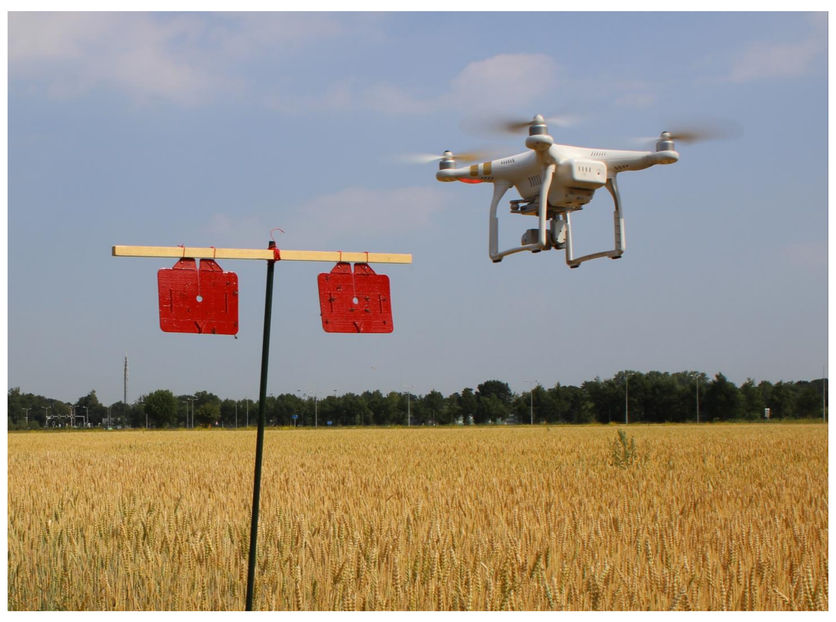

Figure 3. Phantom 3 UAV taking photos of sticky traps with *D. suzukii* flies.

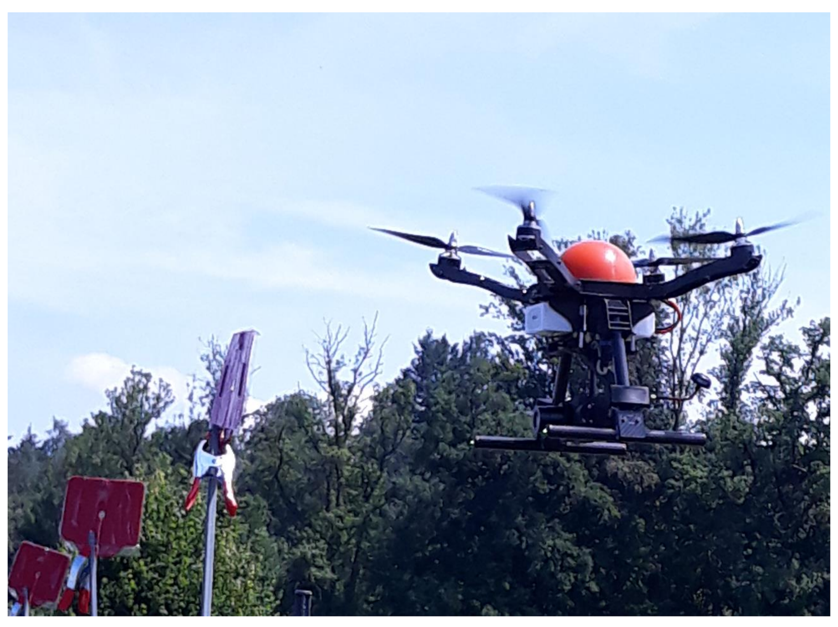

Figure 4. RotorKonzept RKM 4X UAV equipped with a Sony DSC-RX100M4 camera taking photos of sticky traps.

A first trial of experiments with different UAV platforms and cameras was performed to test their ability to collect suitable images in which *D. suzukii* flies can be detected. Images collected by the Phantom 3 (figure 3), did not provide a quality that was high enough for detection of *D. suzukii* flies. The UAV in figure 4, carrying a 20 MP camera was able to take photos of a sufficient quality to detect *D. suzukii* flies (figure 5).

Results – Training accuracies

Training (transfer learning) was performed using a GeForce GTX 1080 Ti GPU. AlexNet and GoogLeNet were trained on two classes: a '*Drosophila suzukii* male' class and an 'other' class. 70% of the 12,000 images were used for training and 30% for validation.

- AlexNet was trained with an accuracy of 79.95%
  - Trianing was done for 30 epochs and took 65 minutes.

- GoogLeNet was trained with an accuracy of 82.16%.
  - Training was done for 30 epochs and took 2305 minutes.

Results – Detection of *Drosophila suzukii* in UAV images

Figure 5 shows the detection of *D. suzukii* flies using AlexNet and GoogLeNet in an image collected by a UAV. Both classifiers were able to detect several of the *D. suzukii* flies, however, they both also produced multiple false detections and misclassifications.

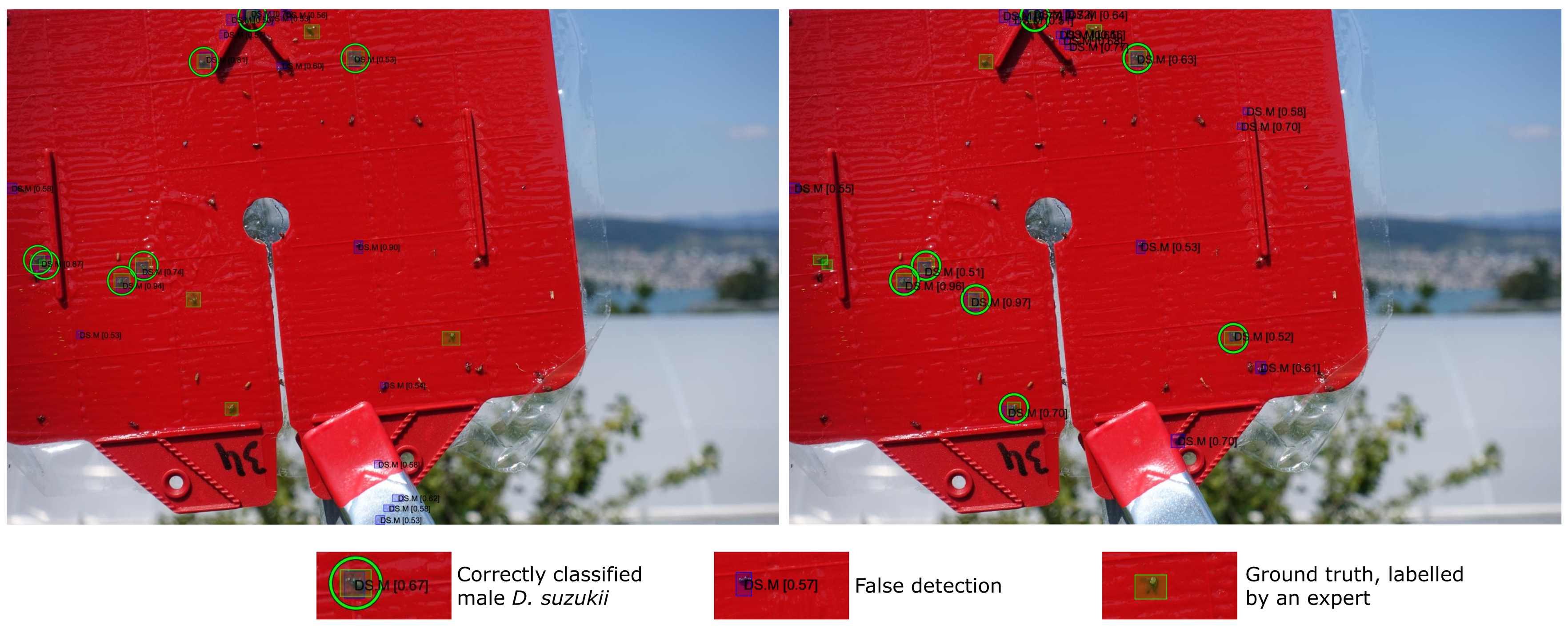

Figure 5. AlexNet (left) and GoogLeNet (right) classifiers applied to detect *D. suzukii* fruit flies in a sticky trap. The image was taken with a Sony DSC-RX100M4 mounted on a RotorKonzept RKM 4X UAV (figure 4). Initial proposal locations were determined using the SelectiveSearch[3] algorithm.

Conclusions

We were able to detect *D. suzukii* flies on RGB imagery of sticky traps. However, the image resolution and quality needs to be rather high. Therefore, our results indicate the feasibility to detect *D. suzukii* flies with drones equipped with medium priced cameras like the Sony RX100M4. Off-the-shelf systems, such as the Phantom 3, are not able to deliver imagery of high enough quality.

Future steps

- Training different deep learning algorithms for *D. suzukii* detection
- Improve separation between *D. suzukii* and bycatch
- Testing different camera systems
- Autonomously flying platforms
- Integration of detection results in a decision support system

References

1. Krizhevsky, A., Sutskever, I., and Hinton, G. "ImageNet Classification with Deep Convolutional Neural Networks". *Advances in neural information processing systems*. 2012.
2. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., and Rabinovich, A. "Going deeper with convolutions". In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1-9. 2015
3. Uijlings, J., van de Sande, K., Gevers, T., and Smeulders, A. "Selective Search for Object Recognition". In *International Journal of Computer Vision*, 2013.

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